Energy and Buildings 81 (2014) 316–325

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

Nonintrusive disaggregation of residential air-conditioning loads from sub-hourly smart meter data

Krystian X. Perez [a,c], Wesley J. Cole [a,c], Joshua D. Rhodes [b,c], Abigail Ondeck [a,c], Michael Webber [b,c,d], Michael Baldea [a,c,e], Thomas F. Edgar [a,c,d,*]

[a] McKetta Department of Chemical Engineering, The University of Texas at Austin, Austin, TX 78712, United States
[b] Department of Civil, Architectural & Environmental Engineering, The University of Texas, Austin, TX 78712, United States
[c] Department of Mechanical Engineering, The University of Texas, Austin, TX 78712, United States
[d] Energy Institute, The University of Texas, Austin, TX 78712, United States
[e] Institute for Computational Engineering and Sciences, The University of Texas, Austin, TX 78712, United States

ARTICLE INFO

Article history:
Received 2 December 2013
Received in revised form 19 June 2014
Accepted 21 June 2014
Available online 28 June 2014

Keywords:
Nonintrusive load monitoring
Disaggregation
Residential energy
Air conditioning
Smart meter

ABSTRACT

The installation of smart meters has provided an opportunity to better analyze residential energy consumption and energy-related behaviors. Air-conditioning (A/C) use can be determined through non-intrusive load monitoring, which separates A/C cooling energy consumption from whole-house energy data. In this paper, a disaggregation technique is described and executed on 1-min smart meter data from 88 houses in Austin, TX, USA, from July 2012 through June 2013. Nineteen houses were sub-metered to validate the accuracy of the disaggregation technique. The R^2 value between the predicted and actual A/C energy use for the 19 houses was 0.90. The algorithm was then applied to all houses. On average, daily energy use from A/C increased by 25 ± 11 kWh between a mild temperature day of 15.5 °C (60 °F) and a hotter day of 31.5 °C (89 °F), with an 11 kWh increase just during peak hours (14:00–20:00). Average time operated, number of cycles, and A/C fraction of energy were found to increase linearly with outdoor temperature up to 25 °C (77 °F); a plateau was detected at higher temperatures. The accuracy of A/C disaggregation on 5-min data was found to be comparable to 1-min data. However, 15-min data did not yield accurate results due to insufficient granularity.

1. Introduction

Approximately 40% of power consumption within the United States is due to buildings, a substantial share of which is due to heating, ventilation and air conditioning (HVAC) [1]. Residential use accounts for approximately one half of building energy use. The load placed on the grid by residential consumers is highly variable and strongly influenced by weather and human activity patterns. For warm climates, such as the southern United States, residential electricity use peaks in the later afternoon hours (16:00–19:00) during summer months, reaching values over five times higher than spring day mornings [2]. The combined effect on the grid causes substantial increases in power demand (see Fig. 1 [3]). Meeting such fluctuations in demand is challenging for grid operators and requires excess capacity from generation facilities to be available. Reducing the high variability in residential energy use can increase the uniformity of energy demand on the grid ("leveling the load"), which reduces reliance on less-efficient peaking plants. Achieving this goal requires an increased understanding of how residential air-conditioning (A/C) usage for individual houses and entire neighborhoods are affected by external factors.

Dynamic or sub-hourly A/C residential energy use problems remain understudied, partly because the cost to obtain detailed measurements is high. For example, it has been a challenge to obtain some general statistics such as daily A/C runtime or daily number of cooling cycles. While a single house does not have an appreciable effect on the grid, entire neighborhoods, or large groups of houses in aggregate have a significant impact. An improved understanding of the effect of external temperatures on residential energy consumption will create more accurate predictions of energy use and better dynamic residential models. Improved models will establish a reliable means to evaluate the effectiveness of thermal storage, district cooling and other large-scale approaches for leveling peak loads [4–8]. This analysis seeks to fill this knowledge gap through the use of newly available smart meter data.

* Corresponding author at: McKetta Department of Chemical Engineering, The University of Texas at Austin, Austin, TX 78712, United States. Tel.: +1 512 471 3080.
E-mail address: tfedgar@che.utexas.edu (T.F. Edgar).

http://dx.doi.org/10.1016/j.enbuild.2014.06.031
0378-7788/

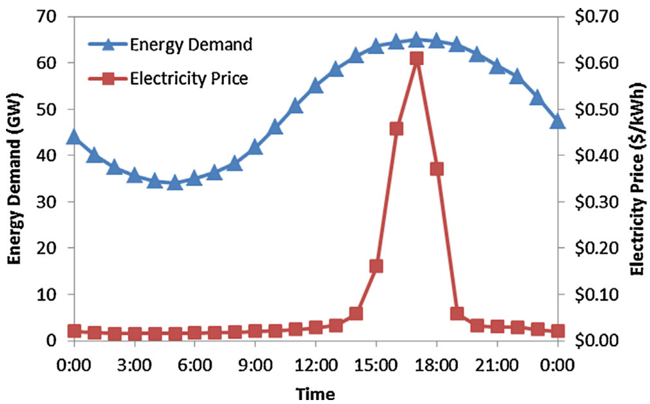

Fig. 1. System-wide energy demand and day-ahead settlement point prices from the Electric Reliability Council of Texas (ERCOT) for June 25, 2012 shows great variability throughout the day [3]. Peak electricity is the most expensive.

Smart meters allow the derivation of valuable information about residential A/C energy use through non-intrusive load monitoring (NILM). However, most meters report solely the whole-house energy use every 15 min. This information is useful in demand-response systems for energy providers; however, most residential loads (including HVAC systems) cycle or operate at much higher frequencies, and their operation and individual energy use can be difficult to estimate from such data. Sub-metering specific circuits such as the A/C is expensive. NILM mitigates this problem by employing algorithms to extract the A/C usage from the whole-house measurements provided by the smart meter.

The NILM method was first described by Hart in 1970 [9]. Hart proposed that an edge-detection algorithm be applied to energy profiles at 1-s time intervals. The algorithm would then segment the profile into periods in which the power is steady (the input does not vary by more than a specified tolerance) and periods in which it is changing. The changes in power were clustered so that “on” and “off” clusters match in relative magnitude. Appliances were then identified using a priori knowledge from direct or indirect measurements. Iterations of this concept by other researchers follow a similar pattern by first developing a library of signatures to identify appliances, through either direct measurements or the application of edge detection [10–17]. Other NILM techniques have been implemented in many ways, including the added use of voltage and current values to better define electronic signatures [18–22]. Then, using various mathematical techniques, changes in power consumption are paired to appliances. A review on NILM techniques was recently published by Zeifman et al. [23], so interested readers are directed there for more information.

The technique used in this paper is different from previous methods in that it is only concerned with the A/C use. One of the challenges in Hart’s method is that it used clustering to match changes in power of on and off events, which required previous knowledge of devices to accurately pair behaviors to devices. By focusing exclusively on A/C energy, this new technique can be accurately tuned for any house to separate just A/C energy use. Rather than pair on and off power events, this technique uses edge detection and *k*-means clustering to find key parameters on A/C behavior. The parameters are then used to identify A/C on and off events.

The purpose of this research is twofold: (1) to develop an algorithm to disaggregate A/C energy use from sub-hourly whole-house energy data and (2) to derive A/C usage information for a residential neighborhood. Because mass installation of smart meters has not occurred until recently, the application of NILM to multiple houses has not been evaluated. The Pecan Street Research Institute has provided unique access to sensors that collect data at 1-min intervals, which is granular enough to implement disaggregation [24].

Table 1
Mueller houses’ basic characteristics [24].

Audit field	Average	Median	St. Dev.
Year built	2008	2008	0.7
Number of levels	1.7	2	0.5
Conditioned area (m^2)	192.5	192.1	50.0
A/C capacity (kW)	10.6	10.6	2.8
A/C efficiency (EER)	10.6	11	1.4
A/C age	2008	2008	0.7
HVAC duct *R*-value	6.8	6	1
Duct leakage (%)	15.5	15	3.8

Since A/C is a dominate feature in the energy profile at 1-min intervals, the on/off events of an A/C unit can be detected. A statistical analysis evaluates the accuracy of utilizing a general disaggregation algorithm by comparing actual vs. estimated A/C use. The algorithm is then applied to a larger dataset of homes in order to estimate A/C usage information for a residential neighborhood.

At the close of the paper, the disaggregation technique is used to perform an analysis on the cost of air conditioning under various rate structures. This cost analysis is only possible using a disaggregated data set, demonstrating the value of the disaggregation technique presented in this work.

2. Methods

2.1. Data

Total energy usage was taken from 88 single-family houses in the Mueller neighborhood in Austin, TX from July 2012 to June 2013. Each house had been metered with an eGauge power monitor that reported whole-house power consumption in watts on 1-min time intervals [24]. Of the 88 houses, 19 had been sub-metered with an additional meter to directly measure power used for the A/C system during the full year. The Mueller neighborhood consists mostly of newer (since 2007), green-built houses and has a large amount of new technology penetration, such as rooftop photovoltaic panels and plug-in vehicles. The houses were equipped with electric A/C cooling units and natural gas heating systems. A/C energy will refer to electricity use used to cool the houses. Table 1 gives results from an advanced energy audit performed by Pecan Street and contains information on general housing characteristics. The statistics (average and standard deviation) refer to the neighborhood containing the evaluated houses. The data set included some errors, such as missing data (17 days total), mislabeled timestamps, meter error reporting constant values (5 days total) and extreme outliers (7 points), which were removed from the evaluated data set prior to analysis.

2.2. Disaggregation outline

This paper uses a non-intrusive load monitoring technique to disaggregate the A/C cooling energy consumption from the 1-min whole-house energy consumption data. In this technique, the magnitude of change in load that signals the A/C turning on or off is found, which is then used to identify on and off events of A/C use. A typical example of daily 1-min data can be found in Fig. 2 for a house that had the A/C sub-metered.

A decision flowchart for the disaggregation process is seen in Fig. 3. The algorithm functions as an edge-detection algorithm, which has been used in other disaggregation techniques [9]. First, energy use data for each house was separated by day from midnight to midnight. The difference in energy between

$$\Delta E_i = E_{i+1} - E_i \tag{1}$$